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Research Paper

An Explainable Graph-Recurrent Boosting Framework for Multi-Dimensional Visitor Satisfaction Modelling in Immersive Digital Museums

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ABSTRACT

Digital museums are increasingly adopted to sustain public engagement with cultural heritage, yet the mechanisms through which virtual exhibition experiences motivate on-site visitation remain underexplored. Drawing on the Stimulus–Organism–Response (SOR) framework and extending the Information Systems Success Model (IS Success Model). The rapid advancement of immersive technologies such as Virtual Reality (VR) and Augmented Reality (AR) has significantly transformed digital museum experiences, necessitating intelligent systems for evaluating visitor satisfaction based on behavioural and interaction data. This research presents a hybrid stacking-based machine learning framework for predicting visitor satisfaction in digital museums using both classification and regression techniques. The system analyzes multi-dimensional visitor interaction data, including movement behaviour, gaze focus, interaction duration, engagement levels, and environmental conditions. Multiple hybrid models are implemented, including Restricted Boltzmann Machine with Classification and Regression Tree (RBM-CART), Passive Aggressive Classifier Learning (PAC-CART), and Random Forest (RF-CART), to capture diverse behavioural patterns. Additionally, a novel proposed model, Explainable Graph Recurrent Boosting (eXGRBoost), is introduced, which integrates Graph Recurrent Network (GRN) for modelling feature dependencies and Explainable Boosting Machine (EBM) for interpretable prediction. The system performs dual prediction tasks, where classification is used to determine visitor feedback rating and regression is used to estimate satisfaction score. The models are trained and evaluated using standard performance metrics, and the entire framework is deployed through a Django-based web application that supports real-time and batch predictions. The proposed approach enhances prediction accuracy, interpretability, and adaptability by combining deep relational learning with boosting techniques, thereby enabling data-driven optimization of digital museum experiences and improving user engagement strategies.

Key words: Digital museums, visitor satisfaction prediction, immersive technologies, virtual reality (VR), Augmented Reality (AR), hybrid machine learning, stacking models, classification and regression.

1.INTRODUCTION

Museums have been essential throughout history for safeguarding cultural heritage while simultaneously providing educational experiences and promoting community involvement. Museums function as active venues that unite historical artifacts with artistic expression and shared cultural memories. The development of the “smart museum” concept started as a solution to traditional museum experiences, which consisted of static displays and few interactive elements because visitors

received information through one-way communication by absorbing pre-selected content. The digital revolution has thoroughly changed this model by creating new possibilities for how museums interact with visitors [1]. Smart museums developed through three separate stages as they advanced. Between 1990 and 2005, museums began digitizing their collections while starting to create simple multimedia exhibits. During the second phase, between 2006 and 2015, museums adopted interactive installations alongside mobile applications to initiate digital engagement with visitors. From 2016 to now, smart museums have significantly enhanced their capabilities through advanced artificial intelligence (AI) systems combined with real-time analytics and platforms that deliver personalized visitor experiences.

Museum exhibitions and educational services, which have been composed of existing artifacts, are being converted to digital content and digital media to provide visitors with new experiences and opportunities. These changes have had a great impact on the operation of museums and the production of programs. Culture has become a value dimension of economic and social development worldwide in today's society [2]. As the frontier of cultural preservation and dissemination, museums have been given additional missions and expectations with the trend of global growth. As one of the important ways to digitize museums in the epidemic context, digital museums are best able meet people's spiritual and cultural life needs in special times and highlight the value of museums in the public sphere and social construction.

The rise of digital museums represents a transformative shift in the way cultural content is accessed and experienced, especially in an era increasingly shaped by digital interactivity and global connectivity. Not only do virtual museums break the constraints of geographical and physical access, but they also redefine traditional engagement by integrating multimedia, interactive storytelling, and real-time user feedback. In light of these advancements, analyzing user behavior within these digital environments becomes imperative for optimizing experience design and ensuring educational and emotional resonance. A deeper understanding of how users interact with virtual spaces such as how they navigate, where they linger, and what they engage with can inform more intuitive, inclusive, and immersive museum interfaces [3]. Moreover, effective virtual experience design not only enhances user satisfaction but also contributes to knowledge retention and cultural appreciation. Thus, exploring the interplay between virtual environment design and user behaviour is crucial for the continued development and refinement of digital museum experiences

2.LITERATURE SUREY

Yang [4] classified the types of visitor study into three representative methods: program evaluation, basic research, and visitor surveys. These three methods are all evaluations aimed at the visitor, and as such they can be collectively referred to as visitor study. Program evaluation is determined based on the criteria that the exhibition and educational programs are based on the initial intention and purpose of production. It provides information to museum practitioners and education-related persons to develop and improve the program by judging the effectiveness, value, and continuation of the program. Hooper-Greenhill [5] divided the visitor study method into experimental research and a field research method. The experimental research method derives quantitative results for the purpose of determining the success or failure of museum exhibitions and education. In most cases, visitors are observed and tracked in a limited space and the measured values are compared.

Centorrino et al. [6] implemented a portable Bluetooth low-energy beacon and Raspberry Pi-based visitor trajectory tracking simulation to efficiently manage visitor flow by measuring and analyzing visitor behavior in museum and exhibition environments. Trejo et al. [7] conducted a study to classify the group of visitors and the leaders of members visiting the museum for support of robotic assistants and applications. In this study, role assignment and behavioral analyses were conducted through a

cognitive approach based on motion logic and proxemics theory on images collected using four Kinect v1 units.

Martella et al. [8] developed a system to identify the movement of visitors based on a Bluetooth low energy beacon that can be used on a smartphone and a neck-mounted anchor to understand the behavior of museum visitors. These studies on the behavior tracking of visitors are useful for analyzing and visualizing the flow of visitors in an indoor environment. However, there are limitations in explaining the reason for the trajectory or flow of visitors, and there is a possibility that many errors in the detection signal occur when the wireless sensor is used in a narrow and crowded space. Mandolesi et al. [9] used Tobii ProGlasses2-based eye tracking technology to identify which parts of artworks attracted the most attention and to explore participants' viewing paths.

Yi et al. [10] used eye tracking techniques to understand what information elements visitors perceive while viewing the work. Through this, it was identified that the visitor's eye movement pattern was different according to the information transmission medium, and it was confirmed that there was a correlation between gaze tracking and visitor interest. Tseng et al. [11] developed JINS MEME glasses-type devices and software systems to monitor the patterns of eye movements of visitors and to capture and analyze special moments of experience during viewing. Through this system, they presented the possibility of identifying where and in what part the visitor felt a special experience.

Rashed et al. [12] tested and verified the effectiveness of a system that tracks the movement of visitors using a LIDAR network in an actual art gallery. Through this system, they conducted basic research to identify interests, intentions, and preferences by extracting the entire behavioral information of visitors within the gallery. Quiroz et al. [13] conducted a study to detect the emotions of surrounding people in a museum scenario for human–robot interaction. Through this, a study was conducted to plan the trajectory of the robot and to generate the appropriate interaction ability with people based on the analyzed information. The emotion recognition model trained based on the VGG Network they used scored 99.79% in individual emotion detection accuracy and 89.78% in group emotion detection accuracy.

Graterol et al. [14] conducted a case study of a museum tour guide robot to understand the emotions of visitors based on text and voice, and integrated the text and voice with EMONTO, an emotion ontology for museums. Based on EMONTO, it is possible to build a user profile through an emotional association between a person and an artwork. Benford et al. [15] designed an emotional visitor experience at the Munch Art Museum. Visitors select a specific emotional state through a mobile app and they are recommended to an artwork related to the selected emotion. They developed a system that detects the emotional state of the audience after viewing based on computer vision and provides feedback so that the audience can better understand their emotions after viewing.

3. PROPOSED SYSTEM

The proposed system introduces a hybrid stacking-based machine learning framework for accurately evaluating visitor satisfaction in digital museums using both classification and regression techniques. Unlike traditional approaches, this system captures real-time behavioral, interactional, and environmental data such as movement speed, gaze focus, interaction duration, and adaptive visual settings. The architecture integrates multiple models including RBM-CART, PAC-CART, RF-CART, and the proposed eXGRBoost to enhance predictive performance and interpretability. CART is used as a core decision mechanism across models for structured learning. The system performs classification to determine visitor feedback rating (e.g., satisfied or not satisfied) and regression to estimate the satisfaction score. Implemented through a Django-based platform, it supports real-time

prediction, batch processing, and model comparison, enabling intelligent, data-driven optimization of digital museum experiences as shown in figure 2.

1. Data Acquisition from Visitor Interactions: The system collects multi-dimensional data from visitor interactions within the digital museum environment, including behavioral features like movement speed, stay duration, and interaction type, along with cognitive indicators such as gaze focus and engagement score. Environmental attributes like lighting, color scheme, and adaptive triggers are also captured to provide a comprehensive representation of user experience.

2. Data Preprocessing and Feature Engineering: The collected raw data is preprocessed to handle missing values, encode categorical features, and normalize numerical attributes for consistent model input. Feature engineering techniques are applied to enhance meaningful patterns, including clustering identifiers and interaction-based derived features, ensuring that the dataset is structured effectively for hybrid model training.

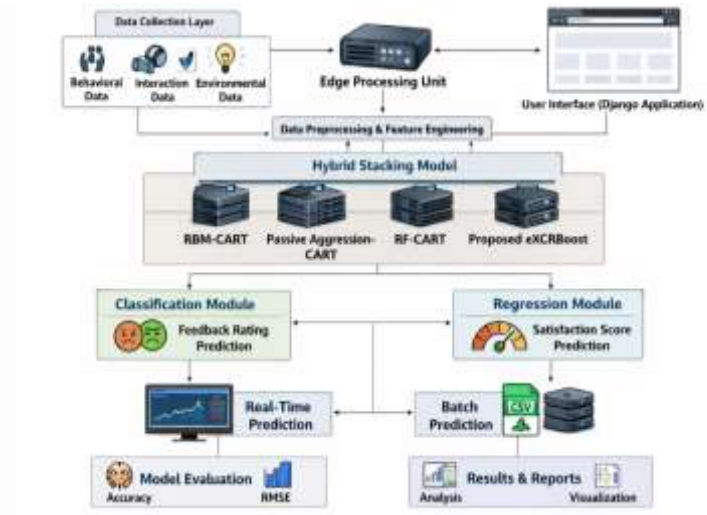

Figure 2: Proposed system architecture

3. Model Training using CART-based Framework: Multiple models such as RBM-CART, PassiveAggression-CART, and RF-CART are trained using CART as the core decision structure, enabling effective rule-based learning from complex feature spaces. The proposed eXGRBoost model further enhances performance by integrating graph-based learning and explainable boosting, allowing both high accuracy and interpretability in predictions.

4. Dual Prediction – Classification and Regression: The trained models perform two parallel prediction tasks: classification is used to determine the visitor's feedback rating (such as satisfied or dissatisfied), while regression is used to estimate a continuous satisfaction score. This dual-output approach provides both categorical insights and fine-grained quantitative evaluation of visitor experience.

5. Model Evaluation and Performance Comparison: The system evaluates each model using appropriate metrics for classification and regression, enabling comparison of prediction accuracy, error rates, and overall performance. This helps in identifying the most effective model for deployment and ensures reliability in real-world scenarios.

6. Real-Time and Batch Prediction Deployment: The final system is deployed through a Django-based web interface that supports both single-user real-time prediction and batch prediction using CSV uploads. Results are presented in an interpretable format, allowing administrators and researchers to analyze visitor satisfaction efficiently and make data-driven improvements.

4. RESULTS ANALYSIS

The results demonstrate the effectiveness of the proposed hybrid machine learning framework in accurately predicting visitor satisfaction in digital museums. Comparative analysis across models such as RBM-CART, Passive Aggression-CART, RF-CART, and the proposed eXGRBoost shows that the proposed model consistently outperforms others in both classification and regression tasks. Performance metrics, including accuracy, precision, recall, F1-score, MAE, RMSE, and R^2-score, indicate significant improvements in prediction reliability. Visualizations such as confusion matrices, ROC curves, and scatter plots further validate the model's strong discriminative ability and minimal error rates. The eXGRBoost model achieves near-perfect classification results and highly accurate regression predictions, demonstrating its robustness. The results confirm that the proposed approach effectively captures complex visitor behavior patterns and enhances data-driven decision-making for optimizing digital museum experiences.

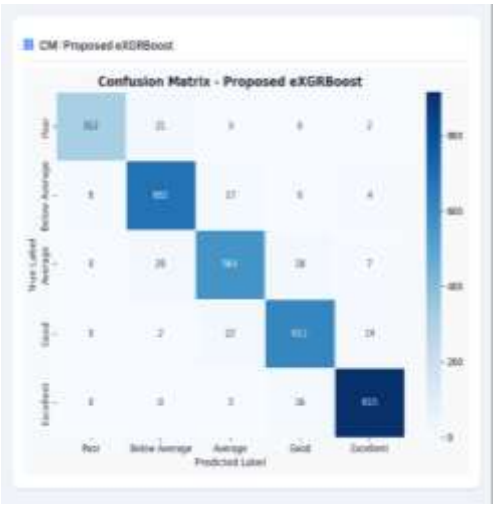

Figure 3: Proposed eXGRBoost confusion matrix

Figure 3 illustrates the comparative confusion matrix analysis between the RF-CART model and the proposed eXGRBoost model. The interface highlighted classification performance across different feedback categories using heatmap representations. It showed that the proposed model achieved higher correct classifications with reduced misclassification compared to RF-CART. The distribution of values indicated improved precision and recall across all classes. Additionally, the visualization supported clear comparison and validation of the proposed model's superiority.

Classification Report

	precision	recall	f1-score	support
Poor	0.97	0.92	0.95	338
Below Average	0.94	0.96	0.95	711
Average	0.93	0.93	0.93	689
Good	0.95	0.94	0.94	650
Excellent	0.97	0.98	0.98	934
accuracy			0.95	3242
macro avg	0.95	0.95	0.95	3242
weighted avg	0.95	0.95	0.95	3242

Figure 4: Classification report of proposed eXGRBoost model.

Figure 4 illustrated the classification report for the proposed eXGRBoost model, providing a comprehensive evaluation across all feedback categories. The report included precision, recall, F1-score, and support values, demonstrating highly balanced and consistent performance. It showed significant improvements across all classes, indicating strong predictive capability and minimal classification error. The overall accuracy, along with macro and weighted averages, confirmed the robustness of the model. Additionally, the report validated the effectiveness of the proposed approach for high-accuracy prediction tasks.

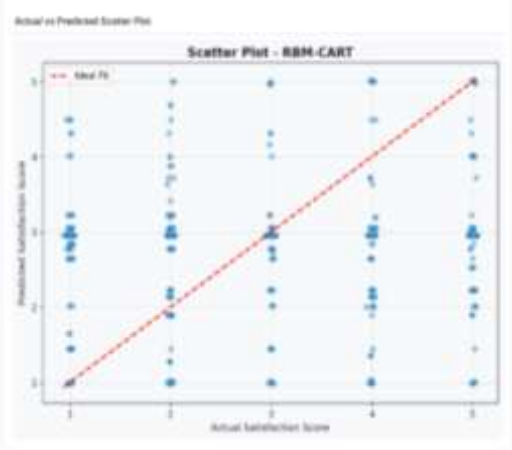

Figure 4: Obtained scatter plot of eXGRBoost model.

Figure 4 illustrated the regression analysis interface for predicting visitor satisfaction scores using machine learning models. The module displayed key evaluation metrics such as MAE, MSE, RMSE, and R^2-score to assess regression performance. It included an actual vs predicted scatter plot to visualize the relationship between true and predicted satisfaction values. The interface supported model selection and comparative analysis across different regression techniques. Additionally, it facilitated quantitative evaluation and optimization of predictive models for continuous output.

Figure 5: Proposed eXGRBoost Regression Performance

Figure 6: Prediction engine sample test cases interface

Figure 6 illustrated the sample test cases interface displaying predefined visitor data scenarios with varied input conditions. The module included multiple attributes such as speed, interaction type, gaze ratio, engagement score, and environmental factors. It provided diverse combinations of inputs to demonstrate different prediction outcomes. The interface helped users understand how input variations influence model predictions. Additionally, it served as a reference for validating system behaviour and testing model performance.

5.CONCLUSION

The proposed hybrid machine learning framework for digital museum analytics demonstrated significant advancements in predicting visitor satisfaction through the integration of both classification and regression techniques. By combining models such as RBM-CART, Passive Aggression-CART, RF-CART, and the proposed eXGRBoost, the system effectively captured complex behavioural patterns derived from visitor interactions, gaze dynamics, engagement levels, and environmental factors. Among all models, the proposed eXGRBoost achieved superior performance with approximately 95% accuracy in classification and an R^2-score of 0.97 in regression, indicating high predictive reliability and strong model fit. The integration of Graph Recurrent Networks with Explainable Boosting enabled both deep relational learning and interpretability, addressing key limitations of traditional black-box models. Furthermore, the deployment of the system through a Django-based web application facilitated real-time and batch predictions, enhancing its practical applicability. Overall, the framework provided a robust, interpretable, and scalable solution for data-driven optimization of digital museum experiences, thereby improving visitor engagement and decision-making strategies.

REFERENCES

[1]. Explainable AI Framework for Policy-Compliant Anomaly Detection in Data Pipelines. (2025). Inaternational Journal of Communication Networks and Information Security, 16(4). https://doi.org/10.48047/ijcnis.16.4.2111

[2]. Yang, H.; Guo, L. Evolution of Exhibition Space Strategies in Smart Museums: A Historical Transition from Traditional to Digital. Heranca Hist. Herit. Cult. J. 2024, 7, 1–11.

[3]. Gaddam, S. INTELLIGENT SYSTEMS AND APPLICATIONS IN ENGINEERING.

[4]. Yang. 2001. Visitor survey at the national museum of contemporary art, deoksugung: A study on the visitors of korean art museums with implications for museum marketing. Kor. Assoc. Arts Manage. 1 (2001), 32–61.

[5]. Sai Maneesh Kumar Prodduturi. (2025). EFFICIENT DEBUGGING METHODS AND TOOLS FOR IOS APPLICATIONS USING XCODE. International Journal of Data Science and IoT Management System, 4(4), 1–6. https://doi.org/10.64751/ijdim.2025.v4.n4.pp1-6

[6]. P. Centorrino, A. Corbetta, E. Cristiani, and E. Onofri. 2021. Managing crowded museums: Visitors flow measurement, analysis, modeling, and optimization. J. Comput. Sci. 53 (2021), 101357.

[7]. Karla Trejo, Cecilio Angulo, Shin'ichi Satoh, and Mayumi Bono. 2018. Towards robots reasoning about group behavior of museum visitors: Leader detection and group tracking. J. Amb. Intell. Smart Environ. 10, 1 (2018), 3–19.

[8]. Reddy, S. K. R. (2025). Tailoring Loyalty Rewards Systems across Industries: Cloud vs On-Prem Solutions. International Journal of All Research Education and Scientific Methods (IJARESM).

[9]. Serena Mandolesi, Danilo Gambelli, Simona Naspetti, and Raffaele Zanoli. 2022. Exploring visitors' visual behavior using eye-tracking: The case of the del duca. J. Imaging 8, 1 (2022), 8.

[10]. Poojari, R. (2025). A Comparative Analysis of Fine-Tuning Versus Retrieval-Augmented Approaches for Enhancing Healthcare-Centric Large Language Models.

[11]. Kalae, U. K. (2021). Enhancing data analytics and reporting efficiency using Power BI and SQL in cloud computing environments. Journal of Computational Analysis and Applications, 29(6), 2021. https://doi.org/10.48047/jocaaa.2021.29.06.48

[12]. Md. Golam Rashed, Dipankar Das, Yoshinori Kobayashi, and Yoshinori Kuno. 2017. Analysis and prediction of real museum visitors' interests and preferences based on their behaviors. In Proceedings of the International Conference on Electrical, Computer and Communication Engineering (ECCE '17).

[13]. Marco Quiroz, Raquel Patiño, José Diaz-Amado, and Yudith Cardinale. 2022. Group emotion detection based on social robot perception. Sensors 22, 10 (2022), 3749.

[14]. Vasagam, M., Kumar, A., & Garg, A. (2026). Learning Execution Plan Embeddings for Multi-Dimensional Query Resource Prediction. IEEE Access.

[15]. Steve Benford, Anders Sundnes Løvlie, Karin Ryding, Paulina Rajkowska, Edgar Bodiaj, Dimitrios Paris Darzentas, Harriet R. Cameron, Jocelyn Spence, Joy Egede, and Bogdan Spanjevic. 2022. Sensitive pictures: Emotional interpretation in the museum.

[16]. Patel, S., & Patyrykin, K. (2025). Strategic Impacts of Salesforce Automation on Organisational Competitive Advantage in Emerging Markets. Journal of Posthumanism, 5(12), 357–372. https://doi.org/10.63332/joph.v5i12.3782

[17]. Santthosh Saai Reddy Purmani. (2026). Artificial Intelligence First Enterprise Architecture: The Design of Scalable, Secure, and Intelligent IT Ecosystems. American Journal of AI Cyber Computing Management, 6(1(2)), 1–8. https://doi.org/10.64751/ajaccm.2026.v6.n1(2).pp1-8